IMAGE REGISTRATION TECHNIQUES FOR MEDICAL IMAGES

Thesis submitted in partial fulfilment of the requirements for the degree

of

Master of Technology

in

Electronics and Instrumentation Engineering

by

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National Institute of Technology Rourkela
Rourkela, Odisha-769008
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Under the Supervision of

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Rourkela, Odisha-769008
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Dedicated

To

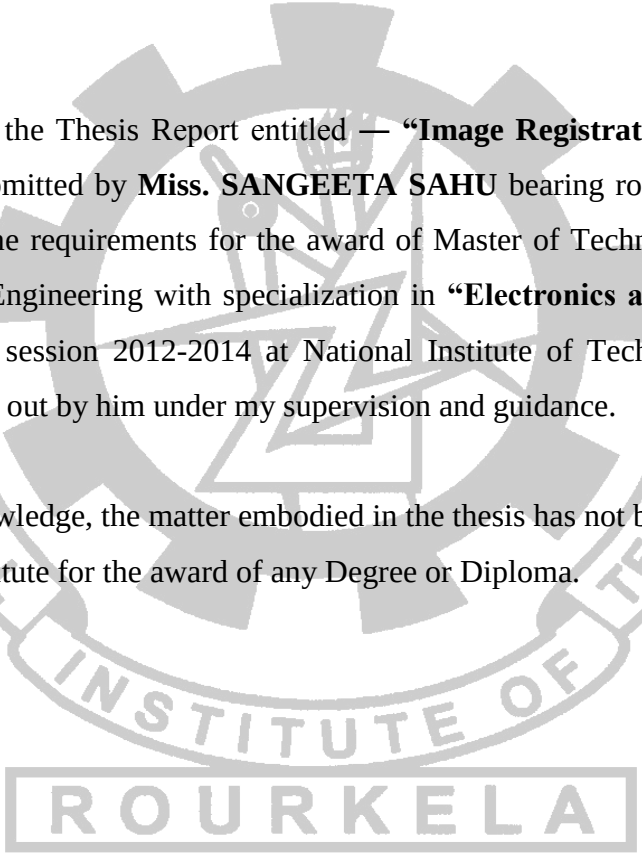
My Teachers,
Family and Friends

Department of Electronics & Communication Engineering
National Institute of Technology, Rourkela

CERTIFICATE

This is to certify that the Thesis Report entitled **— "Image Registration Techniques For Medical Images"** submitted by **Miss. SANGEETA SAHU** bearing roll no. **212EC3379** in partial fulfilment of the requirements for the award of Master of Technology in Electronics and Communication Engineering with specialization in **"Electronics and Instrumentation Engineering"** during session 2012-2014 at National Institute of Technology, Rourkela is authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.



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Date:

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ABSTRACT

Image registration is a primary step in many real time image processing applications. Registration of images is the bringing of two or more images into a single coordinate system for its subsequent analysis. It is sometimes called image alignment. It is widely used in remote sensing, medical imaging, target recognition using multi-sensor fusion, monitoring of usage of a particular land using satellite images, images alignment obtained from different medical modalities for diagnosis of diseases. It is an important step in the field of image fusion and image mosaicing.

In this research work, approaches for image registration are proposed. The image registration methods can be grouped into two classes. One is intensity based method which is based on gray values of the pair of images and the second one is based on image feature which is done by obtaining some features or landmarks in the images like points, lines or surfaces. Edges in the images can be detected very easily in the images. Thus, using these edges some features can be obtained by which we can accomplish feature based registration. But, feature based registration has some limitations as well as advantages. The proposed method employs feature based registration technique to obtain a coarsely registered image which can be given as input to intensity based registration technique to get a fine registration result. It helps to reduce the limitations of intensity based technique. i.e. it takes less time for registration. To achieve this task, the mutual information is selected as similarity parameter.

Mutual information (MI) is used widely as a similarity measure for registration. In order to improve the robustness of this similarity measure, spatial information is combined with normalized mutual information(NMI). MI is multiplied with a gradient term to integrate spatial information to mutual information and this is taken as similarity measure. The registration function is less affected if sampling resolution is low. It contains correct global maxima which are sometimes not found in case of mutual information. For optimization purpose, Fast Convergence Particle Swarm Optimization technique (FCPSO) is used. In this optimization method, the diversity of position of single particle is balanced by adding a new variable, particle mean dimension (pmd) of all particles to the existing position and velocity equation. It reduces the convergence time by reducing the number of iterations for optimization.

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LIST OF ABBREVIATIONS

MI : Mutual Information

NMI : Normalized mutual information

ECC : Entropy Correlation Coefficient

PSO : Particle Swarm Optimization

FCPSO : Fast Convergence Particle Swarm Optimization

CHAPTER 1
INTRODUCTION

Contents

- ✓ *Overview*
- ✓ *Image Matching Technique*
- ✓ *Motivation*
- ✓ *Objective*
- ✓ *Thesis organization*

INTRODUCTION

Registration of images is the bringing of the images into a single coordinate system for its further analysis. It is also known as image alignment i.e. the two different images in different local coordinates have to be aligned in a single coordinate. One of the images is chosen as reference image and another image or the float image will be registered according to the coordinates of reference image.

1.1. Overview

In image processing, when we try to combine the details of the images, we are actually search for the relation between two or more images. The study of this relationship usually becomes manageable once a resemblance is set up between the images. The task of setting up this correspondence is known as registration of images.

Image registration is the task of matching two or more partially overlapping images taken at different time instants or from different observation points. It is a basic image processing technique which is very important step to integrate information from various sensors. It helps to find changes in images which are taken at different time instant. It helps to deduce three-dimensional information from stereo images and to identify model-based objects.

The systems in which image registration is a important constituent includes matching a target with a real-time image of a scene for target recognition, land utilization observation using satellite images, stereo image matching to get shape for autonomous navigation, and alignment of multimodality images for identification of diseases. Image registration is an initial footstep for various applications such as remote sensing and multi-sensor fusion based target recognition. It is required earlier to image fusion or image mosaic.

Registration is done manually as well as automatically[1]. In manual registration, images which are to be registered is taken and human operators manually select corresponding features. For accurate registration results, operators have to choose a plenty of pairs of feature over the full images, which is laborious as well as subjected to irregularity and bounded accuracy. Therefore, it is necessary to find automated techniques which need less or no operator supervision.

1.2. Image Matching Techniques

Image matching techniques can be categorized as gray-scale based matching or image feature based matching.

Gray scale-based matching: Gray scale-based matching examines images as two dimensional signals and make use of statistic approaches to find the correlation functions among signals [2-4], and then obtain their resembling and homonymy points. Gray-scale techniques give good results but take more time as compared to feature based techniques.

Feature-based matching: Feature-based matching finds some features within the images such as points, lines, surfaces and planes [5][6], and then defines properties of those features and then matches the images according to these characteristics. The similar features which are used are textures, shapes and spatial positions. It involves only partial pixels and, thus, reduces matching computation. It gives good registration accuracy because of location sensitivity of the matching properties. The feature extraction lessens the noise effects and increases the compliance with changes in intensity values, morphing and occlusion. The feature based techniques gives less accurate results as compared to intensity based technique.

1.3. Motivation

Edges in the images can be detected very easily in the images. Thus, using these edges some features can be obtained by which we can accomplish feature based registration. But feature based registration has some limitations like low accuracy as well as advantages like less time consuming. Thus, a method was to be searched which employs feature based registration technique to obtain a coarsely registered image which can be given as input to intensity based registration technique to get a fine registration result. The problem with intensity based registration is that it is time consuming. So, the method was required which helps to reduce the limitations of intensity based technique. i.e. it takes less time for registration.

As mutual information may sometimes leads to incorrect registration in intensity based technique, normalized mutual information is taken as search parameter in the next technique as this measure is does not vary with the overlapped area between the images. To make the measure more informative and to make the measure more robust, spatial information is included in the similarity measure to incorporate the intensity information of neighboring pixels. Particle Swarm Optimization (PSO) is a simple and computationally efficient

optimization method. Many modifications have been suggested to the standard particle swarm optimization to find good and faster solutions than the evolutionary algorithms, but those modifications may got stucked in poor region or result in divergence to unstable situations. Thus, modification in the optimization technique was required to avoid this problem and make the optimization process fast.

1.4. Objective

The objective of this work is to develop efficient method of registration of the medical images which uses images' contour information as well as mutual information i.e. a registration method which is a combination of feature based and intensity based method.

The next objective is to develop an effective intensity based registration technique which has sufficient information in the similarity measure and also to reduce convergence time in case of global optimization of this measure.

1.5. Thesis Organization

Including this introductory chapter, the thesis is divided into six chapters:

Chapter 2: Literature Review

In this chapter, we discuss about the literature survey carried out related to the work.

Chapter 3: Registration of medical images using contour information as well as mutual information

In this chapter, registration of medical images is discussed. The images are rotated, scaled and translated with respect to each other. The algorithm uses combination of feature based and intensity based technique. It discusses the steps involved in the algorithm. Also the results and discussions have been given in this section.

Chapter 4: Intensity based rigid registration of medical images

This chapter describes a method to register images using modified normalized mutual information and Fast Convergence PSO optimization. Moreover, it consists of results and discussions.

Chapter 5: Conclusion

This chapter is concluded with the important points of the research work. Furthermore, some suggestions for future work are given.

CHAPTER 2
LITERATURE SURVEY

LITERATURE SURVEY

A lot of work has been done in the field of image registration. The following is a brief introduction of some of the papers.

B.Zitova and J.Flusser presents a basic overview of image registration methods[1]. R.Suganya, Dr.S.Rajaram and K.Priyadharsini used centre of gravity the images for initial registration of images and final registration is accomplished by maximizing the mutual information[2]. L.Junli, C.Rijuan, J.Linpeng and W.Ping proposes a weighted mutual information (WMI) for registration of medical images by which doctors can weightage to the image according to which registration has to be done[4]. I.Misra, S.M.Moorthi, D.Dhar and R. Ramakrishnan proposes an automatic registration method for remotely sensed multispectral images. The method works even if float and reference images are from different sensors[5]. C.S.Qiao uses an image matching technique based on feature extractor such as Harris Operator and proposed a new corner point matching method based on the singular value decomposition[6]. J.Hu, Y.Yang and Z.Su proposes a rapid registration method of the medical images done by using multi-scale transform and contour line[7]. N.A. Al-Azzawi, H.A.M. Sakim, W.A.K.W. Abdullah describes the standard PSO algorithm which is used in the paper to optimize MI. PSO is a global optimization algorithm[8]. F. Maes, A. Collignon, D. Vandermeulen, G. Marchal, and P. Suetens proposes mutual information of the images as the matching parameter and used MI to measure the statistical dependency in the images or redundant information in the image gray values of the corresponding pixels in couple images[10]. L. Ding, A. Goshtasby, and M. Satter proposes a method of registration by selecting templates i.e. subimages from an image and locating the same template in another image of the same view and selecting the centroids of the templates as the control points [11]. J.P.W. Pluim, J.B.A. Maintz and M.A. Viergever gives a survey of various methods involving mutual information and the various classification of the image registration methods. They explained various advantages and disadvantages of taking mutual information as a measure and explains various methods which eliminates the drawback of MI [12]. C. Studholme, D.L.G. Hill and D.J. Hawkes proposes a normalized measure which is invariant to overlapping areas between the images. It is the ratio of the addition of the individual

entropies and the joint entropy[13]. C.Studholme, D.L.G.Hill and D.J.Hawkes proposes a method of registration by computing mutual information of a pair of images by labelling one of the images i.e. labelling of connected region within the images which helps to maintain or increase the measure [15]. J. P.W. Pluim, J.B.A. Maintz and M.A. Viergever describes how gradient information can be included in a similarity measure to increase the information content in the similarity measure[16]. J. Xie , Z. Chen, G. Xu proposes a method to find feature points by wavelet multiscale product and mutual information is used to register feature points and used particle swarm optimization technique to obtain registration parameters[17]. A. Sahu, S. K. Panigrahi, S. Pattnaik proposes a Fast Convergence Particle Swarm Optimization (FCPSO) method which balances the diversity in the position of a single particle by defining a new variable which is the average of the locations of all dimensions of every particle. It improves the functioning of PSO [18].

CHAPTER 3

REGISTRATION OF MEDICAL IMAGES USING CONTOUR INFORMATION AS WELL AS MUTUAL INFORMATION

Contents:

- ✓ *Introduction*
- ✓ *Flow Chart*
- ✓ *Course Registration*
- ✓ *Fine Registration*
- ✓ *Results and Discussion*
- ✓ *Conclusion*

REGISTRATION OF MEDICAL IMAGES USING CONTOUR INFORMATION AS WELL AS MUTUAL INFORMATION

3.1. Introduction

The medical image provides the various details of the patient. It helps a doctor in identification of any disease developed in the patient. In the applications of the medical images, the medical image registration is an important technique because it helps a doctor to observe the development of the disease during some time duration and it also helps a doctor to take an accurate and proper treatment scheme about the disease.

Image registration techniques can be based on intensities or gray-scale of images and features selected in the images whichever is used in registration. Feature based registration results in coarse registration. By using some intensity based method, we can get a fine or accurate registration result. Thus, a method of registration of the medical images based on contour information as well as mutual information of images is proposed.

Feature based registration gives a coarse result due to involvement of partial pixels. Thus, using some intensity based method, a fine or accurate registration can be obtained [7]. This is a registration method for medical images based on contour lines of images and mutual information. First of all, a coarse registration is obtained using image contour lines obtained from canny detector and then fine registration is accomplished using mutual information maximization.

3.2. Flow Chart

Fig 3.1 shows the flow chart for image registration using contour information and mutual information.

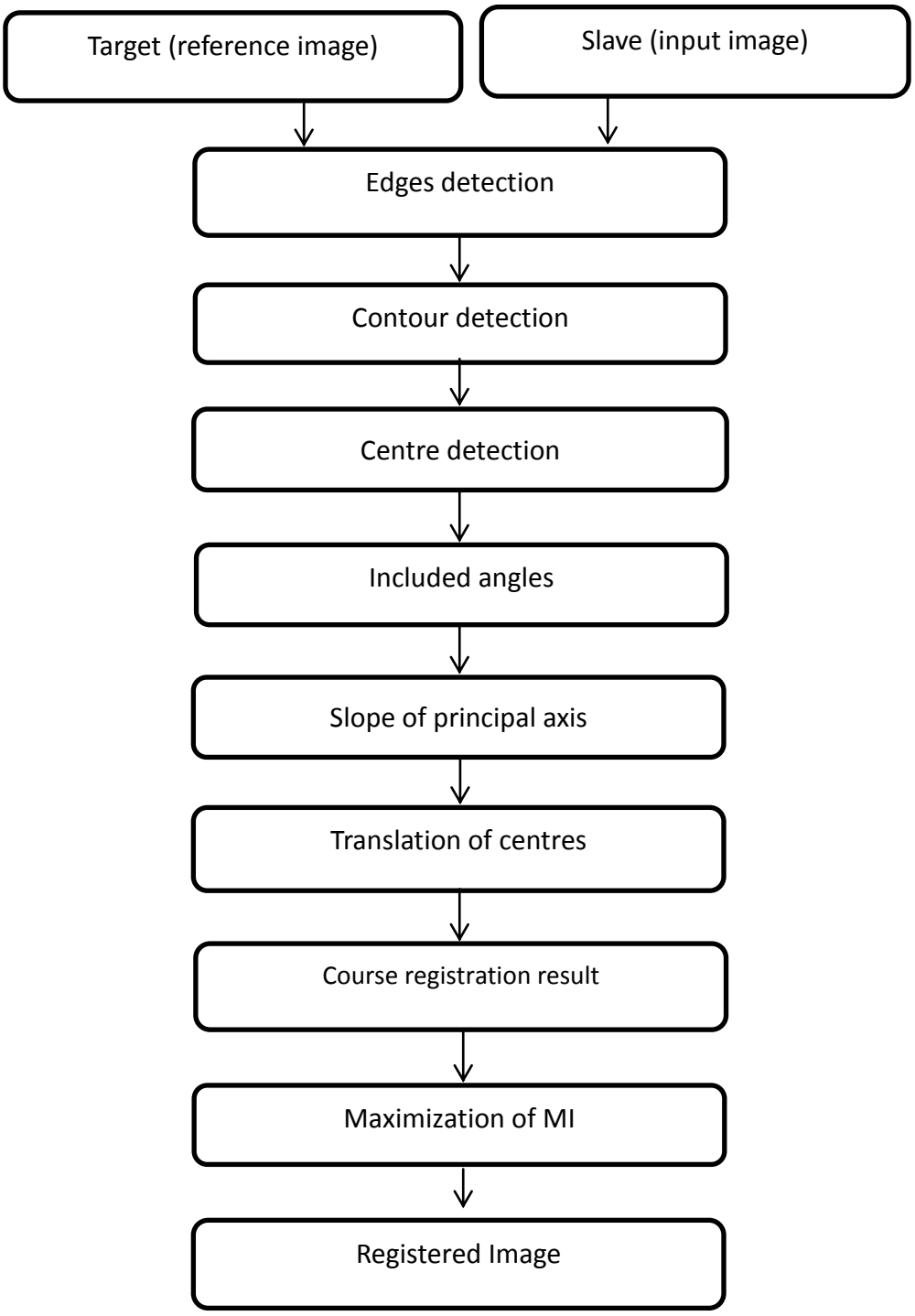


Fig 3.1 Flow chart for image registration.

3.3. Coarse Registration

Coarse registration of image is accomplised by using feature based registration method.

A. Contour Line Extraction

The medical images like brain are rigid in nature, and their edge characteristics are very clear. So extraction of contour of images is easy. Brain images are taken as an example of medical images. Edges of an image are regions with strong intensity contrasts. Detection of edges decreases the quantity of data significantly and removes useless information, and preserves the important structural qualities of an image.

Edge Detection:

Contours of medical images to be registered can be easily extracted by the use of Canny operator. Canny operator, which is known as optimal edge detector, extracts images' edge distinctly and precisely even in the noisy environment. It provides thin edges.

Contour Extraction:

Now, contours of images can be obtained from the edge images which are obtained by using Canny operator by using line by line scanning method. Every row of the edge images are scanned from first to last pixel and only first and last non-zero pixel will be selected. This gives us the contour information of the rows. Similarly for contour information of the columns, every column of the edge images are scanned from first to last pixel, and only first and last non- zero pixel will be selected. Thus, the contour information of a medical image is obtained.

B. Coarse Registration based on contour information of images

Rotation Correction:

Let the pixel coordinates of an images' contour line be $\{(x_{i,}y_i\ )\ i = 1, 2,\ldots n\}$, where n denotes total number of pixels of the contour line. Thus, the centre coordinate of an image can be calculated as given in equation (3.1),

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$
$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{3.1}$$

where,

($\bar{x}$, $\bar{y}$) represent the centre coordinates of the images i.e.

($\bar{x}_r$, $\bar{y}_r$) represent the centre coordinate of the reference image and

($\bar{x}_f$, $\bar{y}_f$) represent the centre coordinate of the float image.

Rotation angle can be obtained by finding the principal axes of the couple medical images. The inertia matrix of contour line of images can be set as given in equation (3.2),

$$I = \begin{pmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \end{pmatrix} \tag{3.2}$$

where,

$$u_{11} = \sum_{i=1}^{N} (x_i - \bar{x})^2$$

$$u_{22} = \sum_{i=1}^{N} (y_i - \bar{y})^2$$

$$u_{12} = \sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y})$$

Based on the inertia matrix calculated by using (2), long and short axes of the images can be found because these axes are actually the two eigenvectors of the inertia matrices. Now, the included angles between the two long axes and the two short axes can be found respectively a as given by equation (3.3),

$$\theta_1 = Cos^{-1}(V_r(1,2) * V_f(1,2) + V_r(2,2) * V_f(2,2))$$
$$\theta_2 = Cos^{-1}(V_r(1,1) * V_f(1,1) + V_r(2,1) * V_f(2,1)) \tag{3.3}$$

where V_r represents eigen vectors of the reference image inertia matrix and V_f represents eigen vectors of the float image inertia matrix. The initial rotation angle is obtained by the averaging the two included angles as given in equation (3.4).

$$\theta = \theta 1 + \theta 2 \tag{3.4}$$

Based on the initial rotation angle, float image can be rotated.

Scaling Correction:

Again the inertia matrix for the rotated float image is calculated by repeating the above procedure. Let $V_{f'}$ be eigen vectors for rotated float image. Then, the slope of the eigen vectors of newly calculated inertia matrix of rotated float image and eigen vectors of reference image is calculated by equation (3.5),

$$\begin{aligned} m1 &= -V(2,1)/V(1,1) \\ m2 &= -V(2,2)/V(1,2) \end{aligned} \tag{3.5}$$

Principal axes can be plotted for both images as principal axis passes through centre coordinate $(\bar{x}, \bar{y})$ and slope of the axes have been obtained. Shift the principal axes in both directions, till this axes just touches the object boundary and thus, boundaries of the object is drawn by the rectangle enclosing the images. By calculating the difference between the values of those shifts, width and height of the object is obtained. The ratio of width of reference to rotated float image gives the scaling factor in y-direction and ratio of height of reference to rotated float image gives the scaling in x-direction. The rotated float image will be scaled by the obtained scaling factor. Now, scaled image is same of same size as the reference image.

Translation Correction:

Again the centre coordinates $(\bar{x}_{f''}, \bar{y}_{f''})$ of scaled float image can be calculated. Now, the translation parameters between the images is calculated as given by equation (3.6),

$$\begin{aligned} \Delta x &= \bar{x}_{f''} - \bar{x}_r \\ \Delta y &= \bar{y}_{f''} - \bar{y}_r \end{aligned} \tag{3.6}$$

According to this translation value, the coarse registration of the pair of medical images has been done.

3.4. Fine Registration

Mutual information (MI) is very popular similarity parameter which is based on Shannon entropy and is widely used in the medical imaging domain. The mutual information is a statistical measure of the mutual dependence of the two images i.e. it represents the statistics correlation of two sets of image data. Registration is assumed to be done when mutual information is maximum i.e. the images should be aligned such that the quantity of information they have about each other is maximum. The mutual information of two images A and B is calculated as given in equation (3.7).

$$I(A, B) = H(A) + H(B) - H(AB) \tag{3.7}$$

where, $$H(A) = -\sum P_A(a) \log P_A(a)$$

$H(A)$ denotes the entropy of image A and the joint entropy $H(AB)$ can be calculated as,

$$H(AB) = -\sum P_{A,B}(a,b) \log P_{A,B}(a,b) .$$

Larger the value of the mutual information obtained in the registration technique, the more precise registration results are obtained.

So, varying the input image over a range of angles, a set of translation is checked for rotated image with respect to input image and the value of translation and rotation for the maximum value of mutual information is noted. Now, the resultant image of coarse registration is rotated and translated by that amount to get fine registration result.

3.5. Results and Discussions

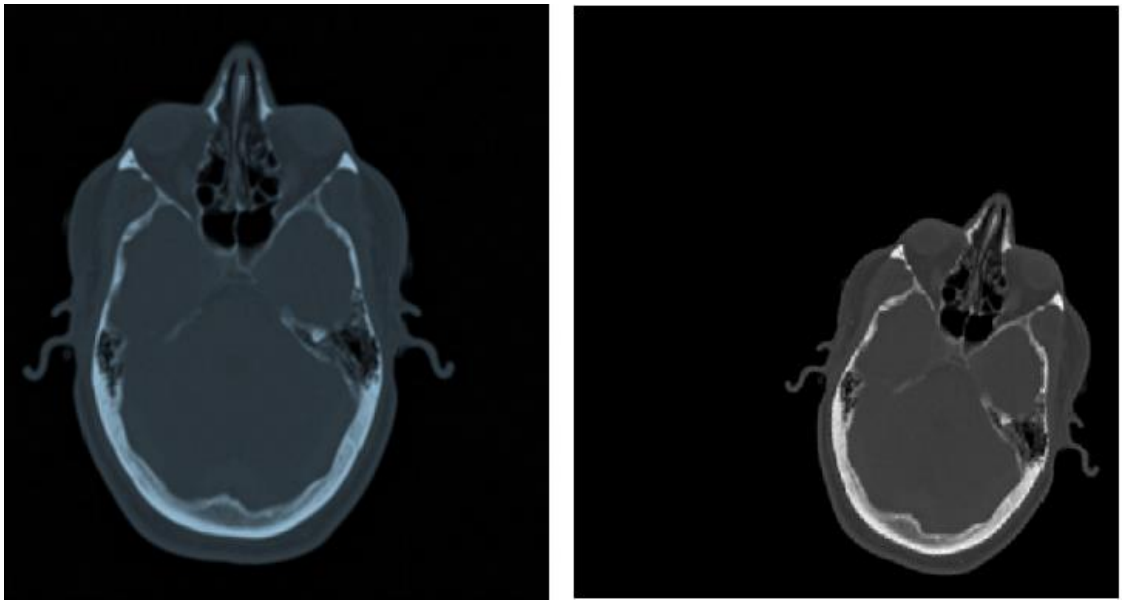
The reference and slave image consists of 256 intensity values i.e. 8 bits gray-scale medical images. Example 1 shows the registration of set of two CT images for up-scaling. Example 2 shows the registration of the set of two CT images for downscaling.

Fig. 3.2 represents the set of two CT images taken for registration. Fig. 3.3 represents the same images which are coloured just to recognize. Fig. 3.4 represents the edge images. Fig. 3.5 represents the contours of images obtained from edge images. Fig.3.6 shows the rotated input image. Fig. 3.7 represents the boundary of images. Fig.3.8 shows scaled input image. Fig. 3.9 represents coarse registration result after translation of scaled image. Fig. 3.10 represents the images after coarse registration. Fig. 3.11 shows the final registered image.

Fig. 3.12 represents the two brain images taken for registration. Fig. 3.13 shows the registration results.

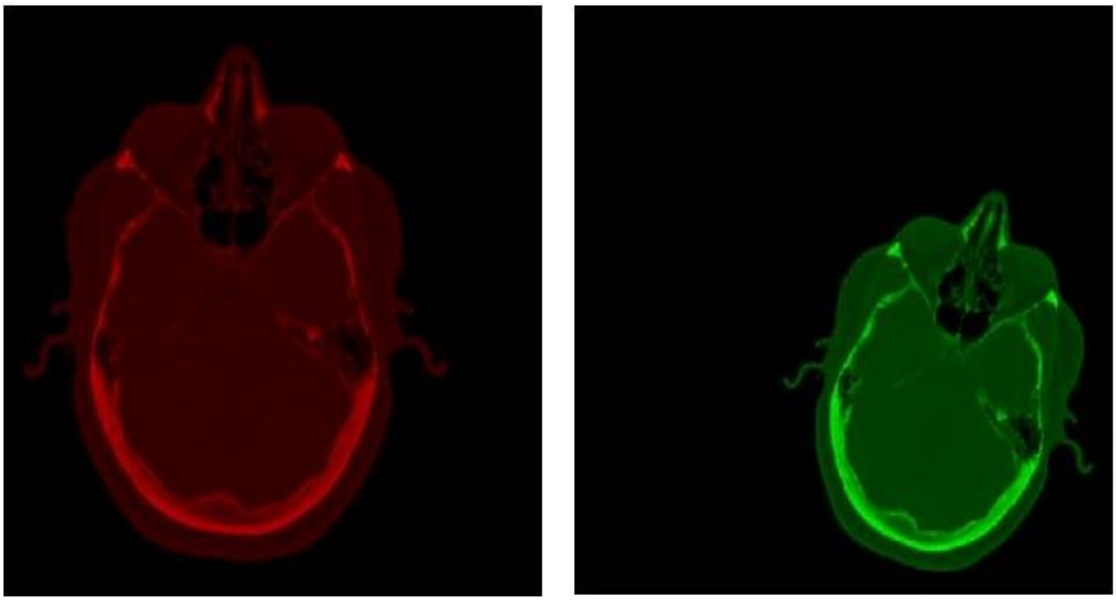
Example 1:

Registration between CT Images for upscaling



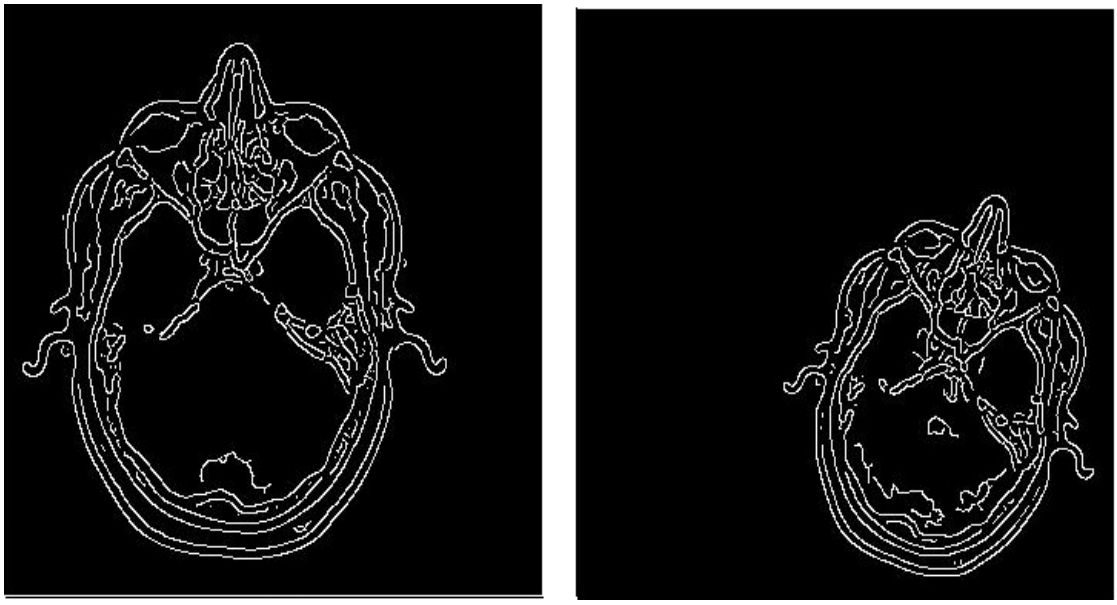
(a) (b)

Fig. 3.2. (a) Reference Image (b) Float Image



(a) (b)

Fig. 3.3.(a) Reference Image coloured as red (b) Float Image coloured as green



(a) (b)

Fig. 3.4 (a)Reference Image (b) Float Image

(a) (b)

Fig. 3.5. (a) Contour of reference Image (b) Contour of float Image

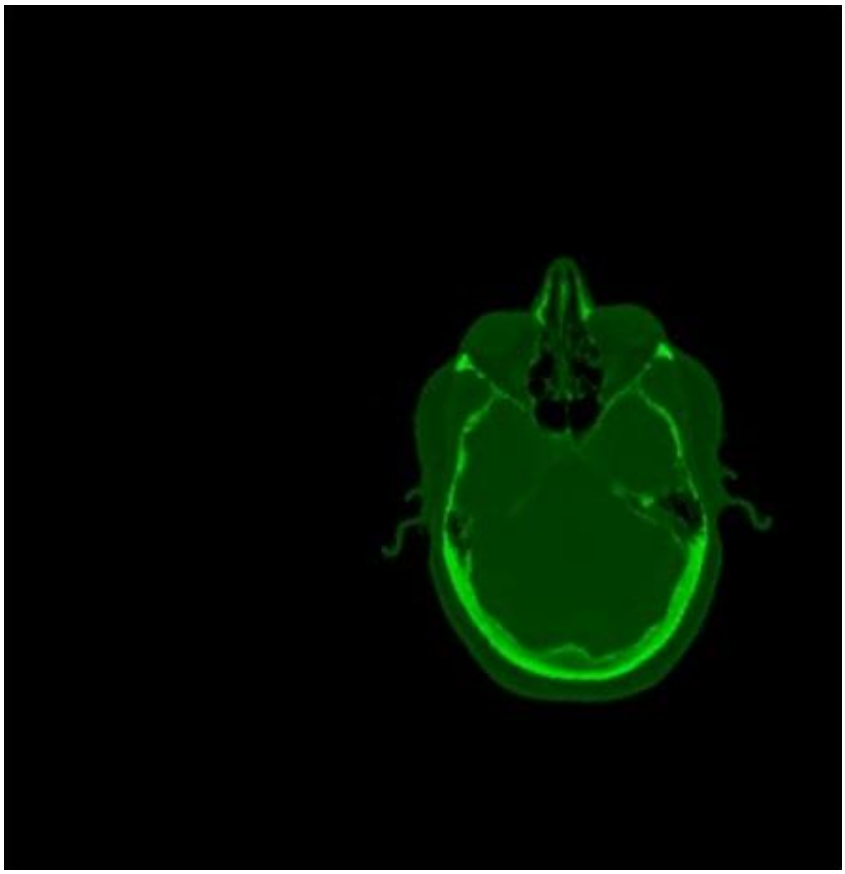
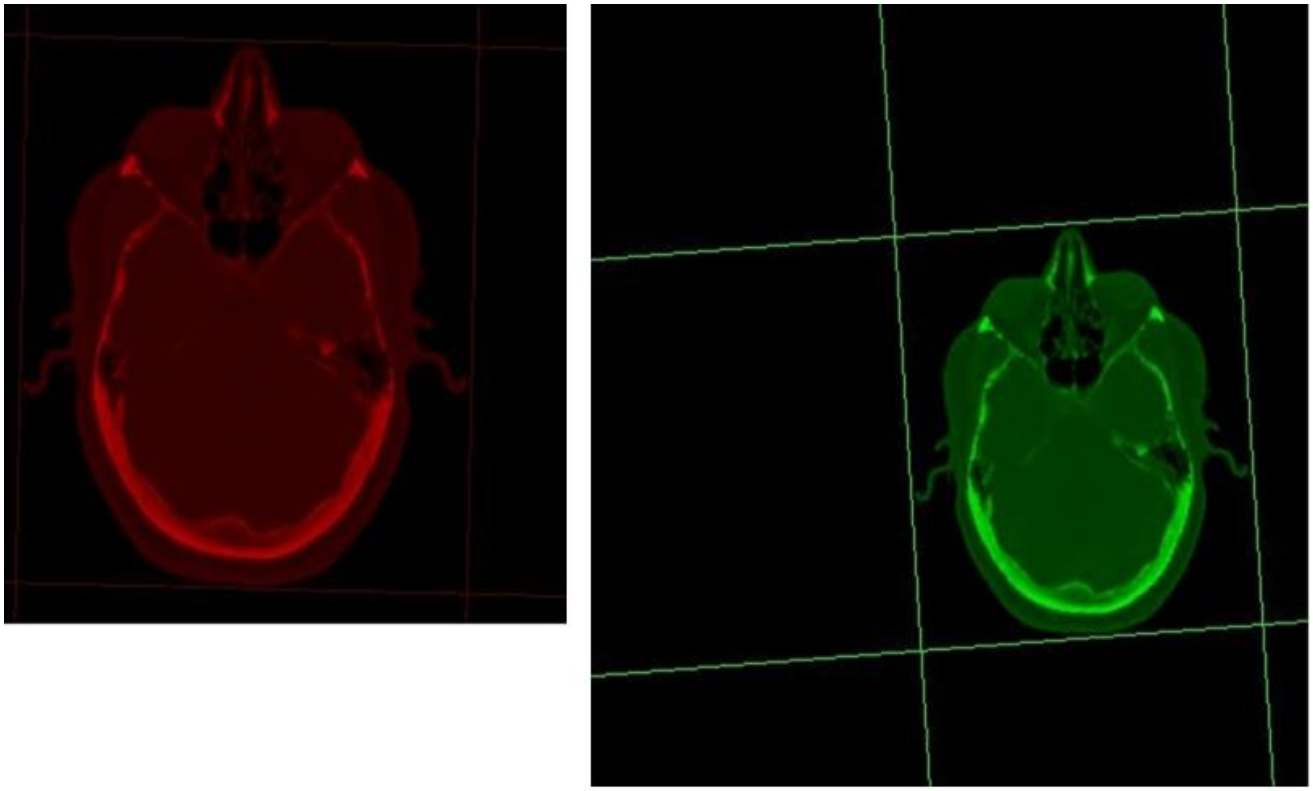


Fig.3.6. Rotated input image



(a) (b)

Fig. 3.7. (a) Reference Image (b) Float Image

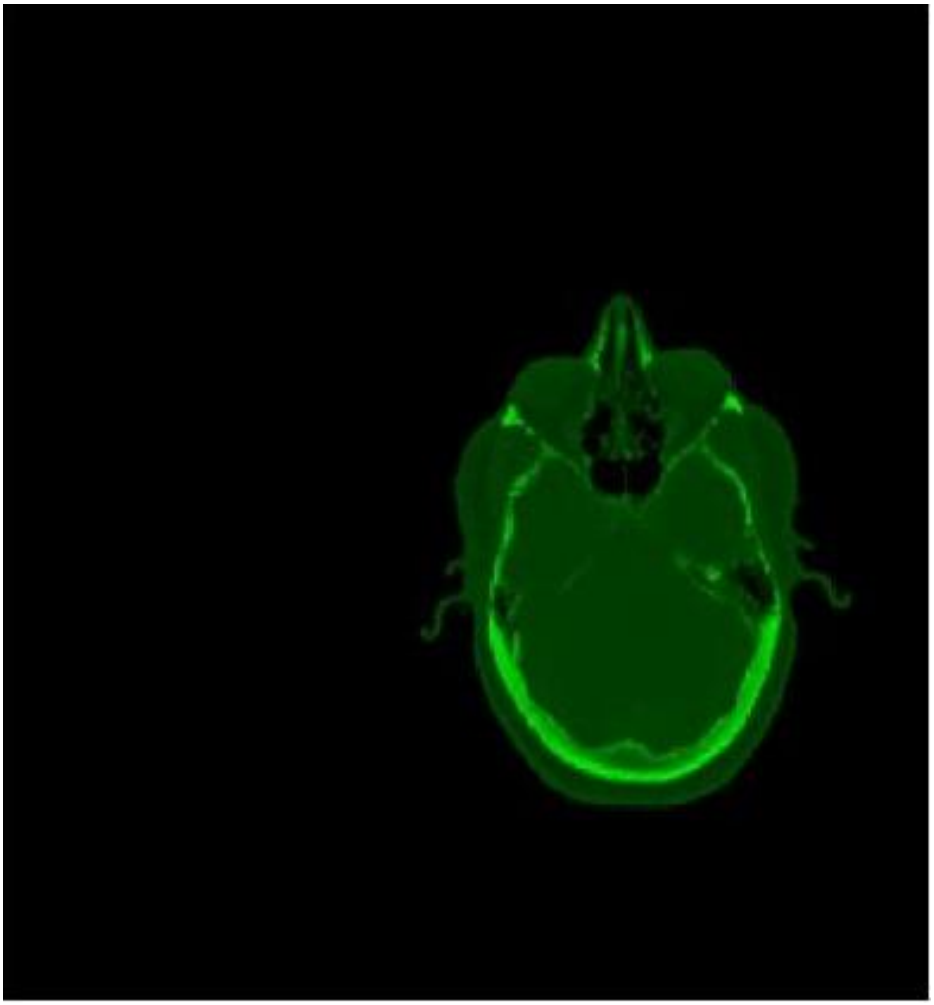


Fig.3.8. Scaled input image

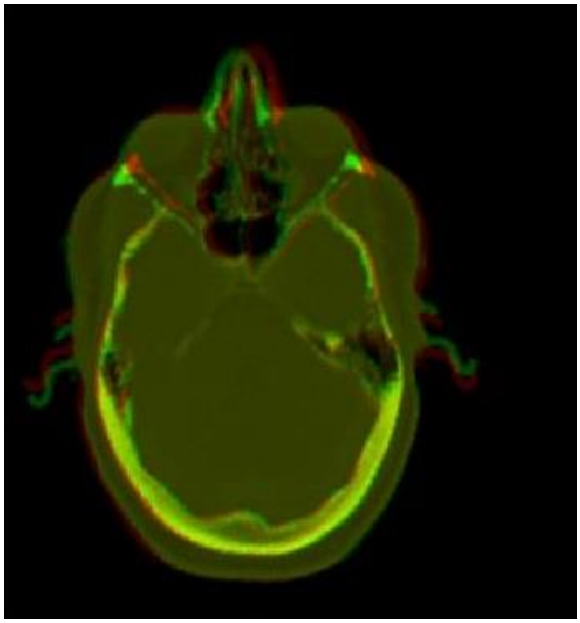
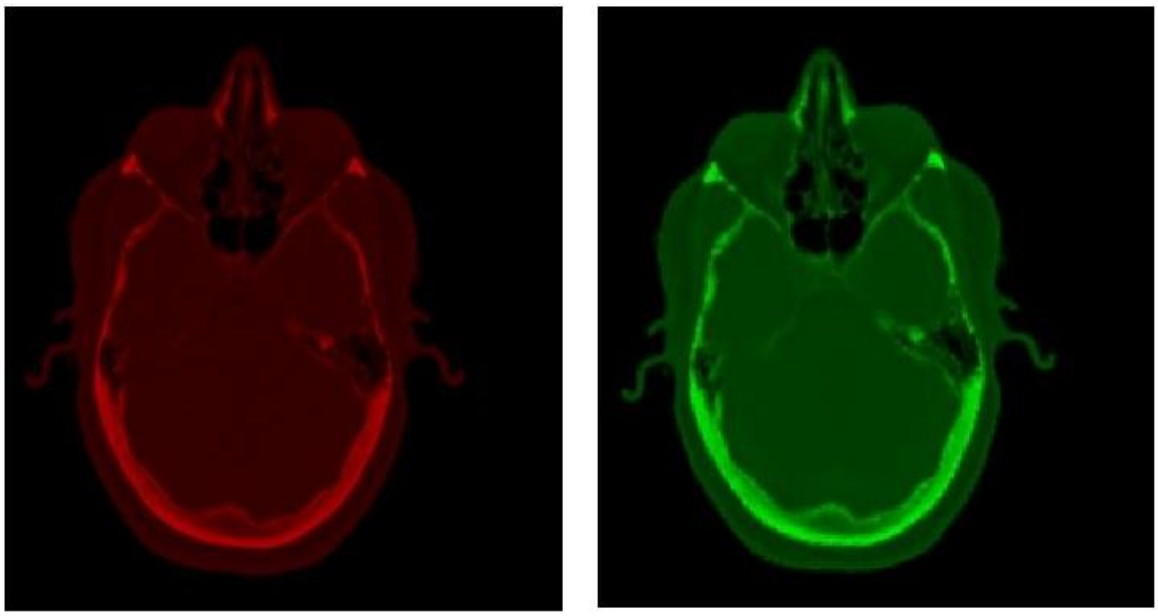


Fig.3.9. Coarse registration result after translation of scaled image



(a) (b)

Fig. 3.10 (a) Reference Image (b) Input image after coarse registration

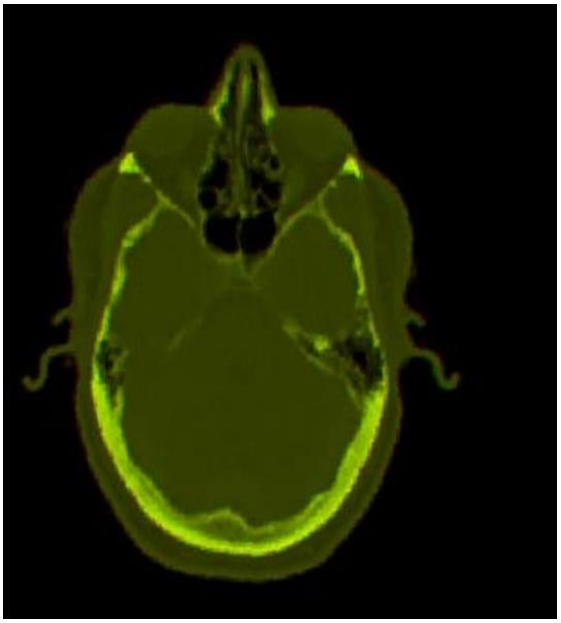
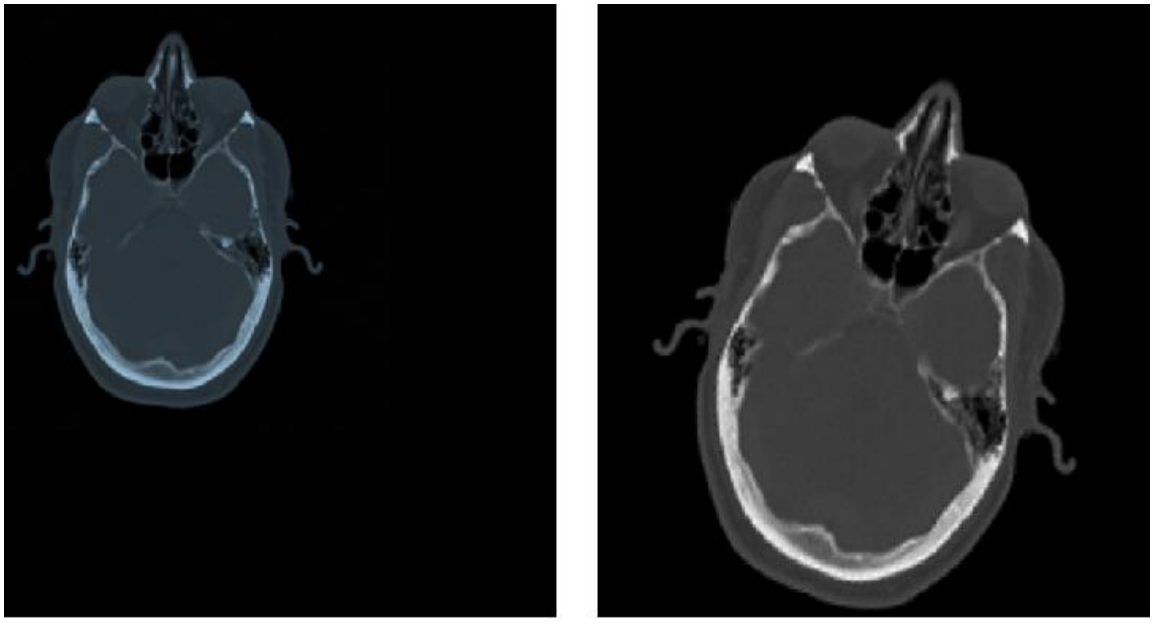


Fig.3.11. Final registered image

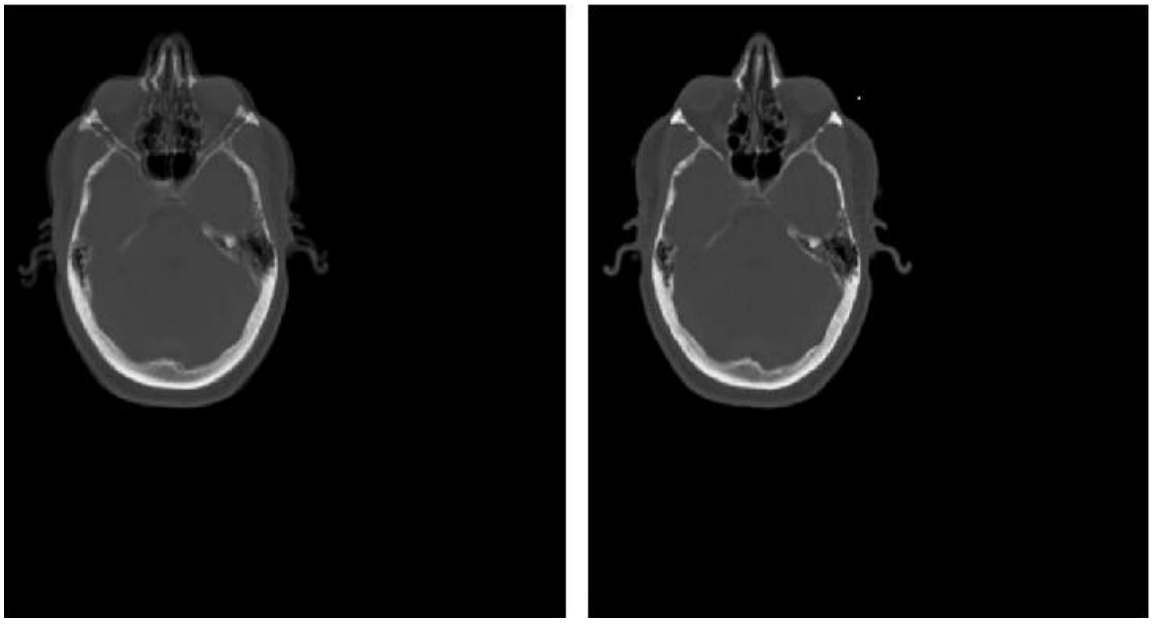
Example 2:

Registration between CT Images for downscaling



(a) (b)

Fig. 3.12 (a) Reference Image (b) Float Image



(a) (b)

Fig. 3.13 (a) Coarse Registration (b) Fine Registration

The registration parameters obtained in the two examples of registration are given in Table I and Table II.

Table I. COARSE REGISTRATION PARAMETERS

Example	Rotation (in degrees)	Scaling		Translation	
		Sx	Sy	x	Y
1	18.78	1.31	1.31	145	249
2	19.34	0.693	0.697	12	34

Table II. FINE REGISTRATION PARAMETERS

Example	Rotation (in degrees)	Translation		Maximum MI
		x	y	
1	-4	12	11	1.7
2	-2	14	26	1.14

This method is a combination the feature and intensity information of the images. So, it involves less mathematical complexity. In feature-based method, partial pixels are selected and thus, calculations are reduced and in intensity-based method, mutual information is to be calculated over a small range of angles as the course registration gives us an approximate result.

3.6. Conclusion

A method of registration of the medical images based on contour information and mutual information of the images is proposed. The feature as well as intensity information of the images are used effectively in the proposed work. The result shows that the proposed approach involves less complexity and is an effective medical image registration method.

CHAPTER 4
INTENSITY BASED RIGID REGISTRATION OF MEDICAL IMAGES

Contents

- ✓ *Introduction*
- ✓ *Flowchart*
- ✓ *Method*
  - *Mutual information*
  - *Including gradient information*
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- ✓ *Results and Discussions*
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INTENSITY BASED RIGID REGISTRATION OF MEDICAL IMAGES

4.1. Introduction

Mutual information is an gray-scale based similarity parameter used in case of both monomodal as well as multimodal images[8][9][10][11]. It does not require any features such as points or surfaces as feature based registration technique which leads to coarse registration. In spite of the promising results given by mutual information, sometimes it results in misregistration of images i.e. it fails occasionally. This occurs when the resolution of the images is low, when little information is present in the images or when there is less overlapping region between the images. The mutual information measure is influenced by size of the overlapping part of the images in two ways[12]. Decreasing the overlap area decreases number of samples. If number of samples reduces, it reduces the statistical power of probability distribution estimation. Futhermore, if misregistration rises, the mutual information measure can become high because increasing misregistration matches with reducing overlap. This happens when the corresponding area of object and background becomes equal and the sum of the marginal entropies increases rapidly in comparison to joint entropy. A normalized measure of mutual information is proposed by Studholme [13]. Normalised mutual information(NMI) is less affected by changes in overlap and is expressed by equation (4.1).

$$NMI(A,B) = \frac{H(A) + H(B)}{H(A,B)} \tag{4.1}$$

Improved results are obtained if normalized measure is taken for rigid registration of multimodal images[13].

In mutual information found from Shannon entropy[14], the dependence of the intensity values of the adjacent pixels is completely neglected. But, the original Shannon entropy definition includes the dependence of prior signals. However, the definition of Shannon entropy used in applications is for independent consecutive signals. This idea of independence of signals does not apply in case of medical images. The dependence of the intensity values of adjacent pixels is actually termed as spatial information of the images. Thus, including the spatial information

with mutual information[15] can improve registration results. So, to integrate spatial information, mutual information can be combined with parameter obtained from the gradients at corresponding points. This parameter aligns gradient vectors of large magnitude and of same orientation[16].

Particle Swarm Optimization(PSO) is a global optimization technique which is widely used[17]. But, it takes large time to converge. So, to reduce the number of iterations, Fast Convergence Particle Swarm Optimization[19] is used in this method.

4.2. Flowchart

Flow chart of the method is given in figure 4.1.

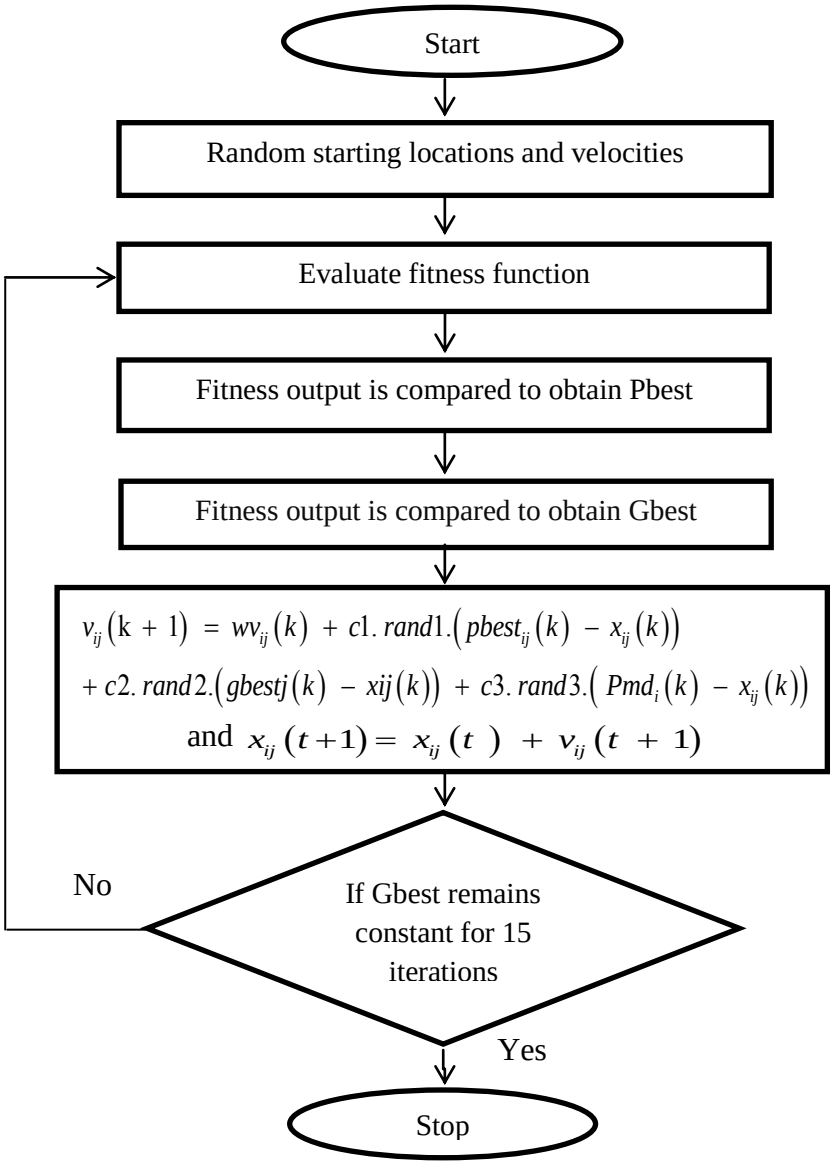


Fig.4.1. Flowchart of method

4.3. Methodology

The method used is the combination of the combined measure of normalized mutual information as well as the gradient information and the technique used for optimization purpose.

A. Mutual information

Mutual information of the two images is the addition of the individual and joint entropies of the two images. Entropy is, how much the probability distribution of the images disperses. When a probability distribution has acute and dominant peaks, entropy will be minimum. When every outcome has equal chances of occurring i.e. for a uniform distribution, entropy will be maximum. By arranging the probability distribution of the images intensity values, the entropy of the images is calculated. The Shannon entropy for probability distribution is defined as given in equation (4.2),

$$H = -\sum_{i,j} p(i,\mathrm{j}) \log \mathrm{p(i,\ j)} \tag{4.2}$$

i.e. $H(A)$ denotes the individual entropy of image A and

$H(B)$ denotes the individual entropy of image B and are calculated as given by equation (4.3) and (4.4),

$$H(\mathrm{A}) = -\sum P_A(\mathrm{a}) \log P_A(\mathrm{a}) \tag{4.3}$$

$$H(\mathrm{B}) = -\sum P_B(\mathrm{b}) \log P_B(\mathrm{b}) \tag{4.4}$$

$H(A,B)$ is the joint entropy of image A and image B, i.e. the entropy of the joint probability distribution of the intensities of image A and image B.

By computing a normalized joint histogram of the intensities of the two images, joint probability distribution is estimated. It is expressed as given in equation (4.5).

$$H(A,B) = -\sum P_{A,B}(a,b) \log P_{A,B}(a,b) \tag{4.5}$$

The mutual information $I(A,B)$ of two images A and B intermingles the individual and joint entropies of the images and is given by equation (4.6).

$$I(A,B) = H(A) + H(B) - H(A,B) \tag{4.6}$$

Images are correctly registered when MI of images is maximum. This suggests, there should be a balance between joint entropy minimization and marginal entropies maximization. The joint entropy will be minimized if the joint distribution is minimum dispersed, i.e. when a distribution has less number of acute and dominant peaks. This coincides with registration. In case of improper alignment of the images, new pairs of grey values will be introduced which decreases the probabilities of the 'correct' combinations resulting in more dispersed joint probability distribution. But, the mutual information measure is affected by overlapping areas between the images and normalized MI can overcome this problem[12] and the entropy correlation coefficient(ECC) is different form of normalised MI given in equation (4.7),

$$ECC = 2 - \frac{2}{NMI} \tag{4.7}$$

$$i.e.\ \ ECC(A,B) = \frac{2 * I(A,B)}{H(A) + H(B)}$$

B. Integrating gradient information

Image areas with strong intensity contrasts are the areas of high information value as it denotes transition of tissues. The gradient is computed on spatial domain. Normalised mutual information is modified to integrate spatial information existing in the images. i.e. normalised mutual information is multiplied with a gradient term. This term is based on both the magnitude and the orientation of the gradient vectors[16]. Directly calculating normalized mutual information of gradient images can also be done to incorporate spatial information. But, it can result in narrow attraction range of registration function and a lot of information of the intensity values is rejected. Thus, a combination of normalised mutual information i.e. Entropy Correlation Coefficient and spatial information is used. The gradient vector is calculated for every sample point 'a' in one image and the corresponding point 'b' in another image, which is obtained by geometric transformation of 'a'. The gradient vector is obtained by calculating two partial derivatives in both x and y direction. To find the gradient vector, the image is convolved with the first derivatives of a Gaussian kernel of scale σ. σ can be taken in range of 0.5 to 1. The angle $\theta_{a,b}(\sigma)$ within the gradient vectors can be calculated as given by equation (4.8),

$$\theta_{a,b}(\sigma) = \arccos\left(\frac{\nabla a(\sigma).\nabla b(\sigma)}{|\nabla a(\sigma)||\nabla b(\sigma)|}\right) \tag{4.8}$$

with ∇a(σ) denotes the gradient vector at point a of scale σ and mode denotes magnitude.

In different modality images, the various tissues have different intensities. So, the gradient of the images points in dissimilar directions. However, since the different modality images represent the identical anatomical structures, gradients of the two multimodal images will have the same orientation; either it can be in same or reverse directions. Weighting function *w* is used so as to adjust both very small angles as well as large angles that nearly equals 180 and is given by equation (4.9).

$$w\left(\theta_{a,b}(\sigma)\right) = \frac{cos\left(2\theta_{a,b}(\sigma)\right) + 1}{2} \tag{4.9}$$

But, because of difference in imaging processes of different modalities, it is not essential that different modality images represent the same transitions of tissues. Therefore, strong gradients in a certain modality may not be present or less significant in another modality. But, we have to include strong gradients of the both images. Thus, minimum of the gradient magnitudes is multiplied by the angle function. Gradient term is the summation of the resulting product for all samples which is multiplied by the normalised mutual information measure. Tissue transitions in both modalities are emphasized. Gradient term may be mathematically expressed as given by equation (4.10),

$$G(A,B) = \sum_{(a,b)\in(A\cap B)} w\left(\theta_{a,b}(\sigma)\right) * min(|\nabla a(\sigma)|,|\nabla b(\sigma)|) \tag{4.10}$$

The combined measure of normalized MI and spatial information is given by equation (4.11).

$$ECCnew\ (A, B) = G(A, B)*ECC\ (A, B) \tag{4.11}$$

C. Optimization

Particle Swarm Optimization[18] is a population-based search technique. Particle Swarm Optimization is both simple and effective. Particles represent a population of possible solutions. Particles are depicted by a position and a velocity vector both. The location of each particle represents a solution. The main logic is that individuals or particles gain experience from the member or particles at the best position to reach the group objective or to reach the

location where there is maximum availability of food. As the population moves towards its objective, each individual adjusts its position according to its own and the adjacent particles experiences. A fitness function is used to search for the best position. The fitness function must be defined by the parameters to be optimized. Every time the loop repeats in simulation, the fitness function can be computed by taking the location of the particles in the search space. Every particle stores the best value found by it so far. The location of the highest fitness value of each particle is called personal best or local best (pbest). The location of the highest fitness value among the particle swarm i.e. among all particles is called global best (gbest). In each iteration, there is exactly one gbest and all the particles are pulled in the direction of gbest location. After finding pbest and gbest values, the particle modify the velocity and position as given by two equations (4.12) and (4.13).

$$v_{ij}(k+1) = w*v_{ij}(k) + c1*rand1*(pbest_{ij} - x_{ij}(k)) + c2*r2*(gbest_j - x_{ij}(k)) \quad (4.12)$$

and

$$x_{ij}(k+1) = x_{ij}(k) + v_{ij}(k+1) \quad (4.13)$$

where,

$v_{ij}(k+1)$ is the particle's velocity i.e. velocity of ith particle at (k + 1)th iteration,

$x_i(k)$ is the solution of current particle i.e. position of ith particle,

$pbest_i$ is the previous best position of the ith particle,

gbest is the global best position achieved by particle swarm till then,

rand1 and *rand2* are random numbers between 0 and 1,

c1 is the cognitive factor or individual learning rate,

c2 is the social constant,

w is the inertia weight,

k is number of iteration i.e. $k = 1,2,\ldots,$

j is the particle dimension.

To control the velocity of a particle, a maximum velocity v_{max} is inflicted on particle's velocity i.e. if any particle moves with a velocity that exceeds the maximum velocity v_{max}, then that particle's velocity is reduced to v_{max}. Each velocity vector is compressed within the limits $[v_{max}, v_{min}]$ to lessen the chances that the particle departs from the position limits.

D. Fast Convergence-Particle Swarm Optimization

In standard PSO, starting particles are evenly dispersed in the search space. The method may get confined in local minima and $pbest_i$ may not get changed for many steps, because of the mutual limitation of variable of each dimensions. It is difficult for the method to run away from the local minima, thus, the correct location will not be obtained.

When the swarm gets updated from the k generation to k + 1, along with the trace of $pbest_i$ and *gbest*, the particles can trace pmd_i which is obtained from the swarm. The new variable pmd_i of ith particles are calculated as given by equation (4.14).

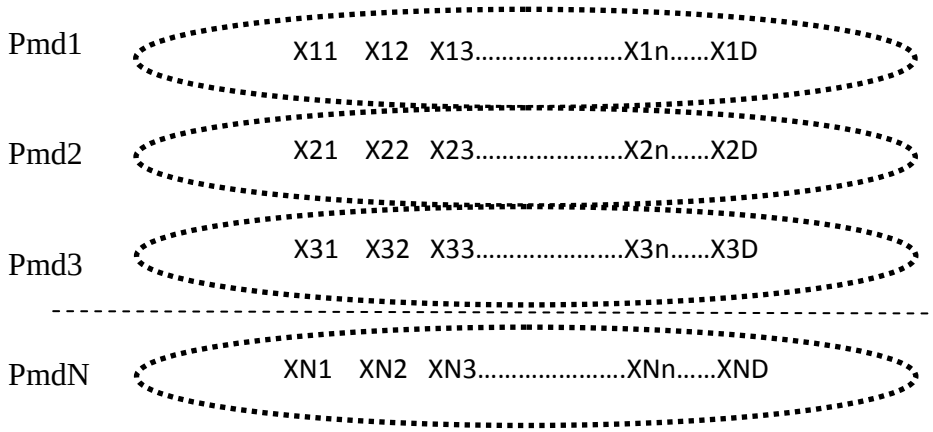


Fig.4.2. Particle mean dimension for n particles

$$Pmd_i = \left(x_{i1} + x_{i2} + \ldots\ldots\ldots\ldots + x_{iD} \right) / D \tag{4.14}$$

where,

D, Particles' dimensions in the swarm and the new velocity and position is represented by equation (4.15) and (4.16) respectively,

$$\begin{aligned} v_{ij}(\mathrm{k}+1) &= wv_{ij}(k) \\ &+ c1.rand1.\left(pbest_{ij}(k) - x_{ij}(k) \right) \\ &+ c2.rand2.\left(gbest_j(k) - xij(k) \right) \\ &+ c3.rand3.\left(Pmd_i(k) - x_{ij}(k) \right) \end{aligned} \tag{4.15}$$

$$x_{ij}(k+1) = x_{ij}(k) + v_{ij}(k+1) \tag{4.16}$$

where,

c3 is the mean best learning factor,

rand3 is the random vector between [0, 1].

Here, c1,c2 and c3 are selected satisfying the equation (4.17).

$$\phi = c1 + c2 + c3 \tag{4.17}$$

where, $\phi >= 4$

After adding pmd_i in the velocity formula, all $pbest_i$, *gbest* and pmd_i gives information to the next generation combinely and thus, the information received from previous generation increases. This method helps to get the favourable solution quickly. Also, the weightage factor of pmd_i , i.e. 'c3' is small. Thus, this term equals disturbance information and increases the diversity between the particles. The *gbest* location improves convergence rate.

However, it decreases the diversity among population which results in local minima. Simultaneously, parameter pmd_i takes the particles to a better location and reduces the chance of attraction of particles towards local minima.

E. Formulation of FCPSO

First of all, some particles are chosen and the number of dimensions for which float image is to be corrected is decided. The experiments are performed by taking 25 particles and 3 dimensions are to be searched i.e. rotation in one plane and translation along two axis. Search space is the limits for the position of particles in which food is to be searched. Search space for particles position is given as [-48 48; -48 48; -25 25] where first column shows minimum limit and second column shows maximum limit for particles position in each dimension. The value of $[v_{\max}, v_{\min}]$ is selected as twice the limits of position for each dimension. Cognitive(c1) and social constant(c2) are given as 1.8 and c3 as 0.4. The particles are allocated random positions at first. The fitness function i.e. ECCnew measure is calculated for those particle locations. The location for the best availability of food i.e. maximum fitness function is saved as gbest and for each particle pbest i.e. the location of best food availability is saved as the initial particle location at first run. The value of pmd is calculated for each generation of particle. The velocity for the particles is calculated by using equation (4.15). If the velocity of the particle obtained is greater than $v_{\max}$, then it is set to $v_{\max}$ and if it is less than $v_{\min}$ then, it is set to $v_{\min}$ .The new locations for the particles are calculated by using

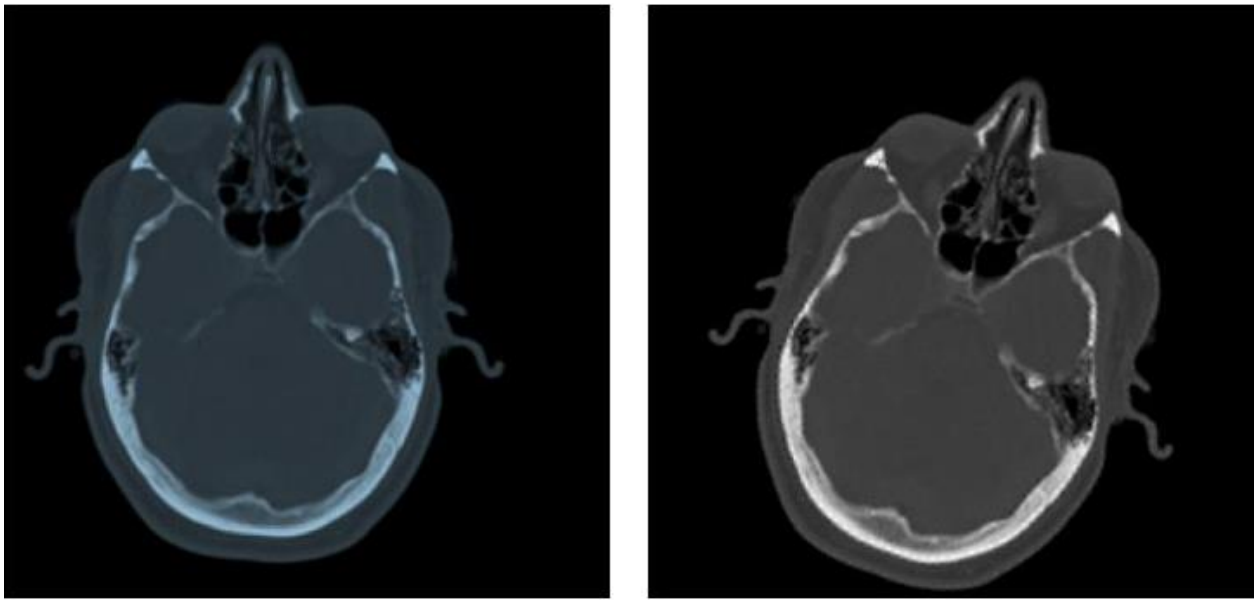
equation (4.16). The fitness function output is then checked. If the new locations give high value then, according to that pbest and gbest are set. The loop was repeated until gbest remained constant for 15 iterations.

4.4. Results and Discussion

The target and slave image consist of 256 intensity values i.e. 8 bits gray-scale medical images. The floating image has some translation and rotation with respect to reference image. Three examples of registration are given. First two examples are for monomodal images and third example is of multimodal registration. Example 1 gives the registration of two CT images. Example 2 gives the registration of two MRI images. Example 3 gives the registration of CT and MRI images.

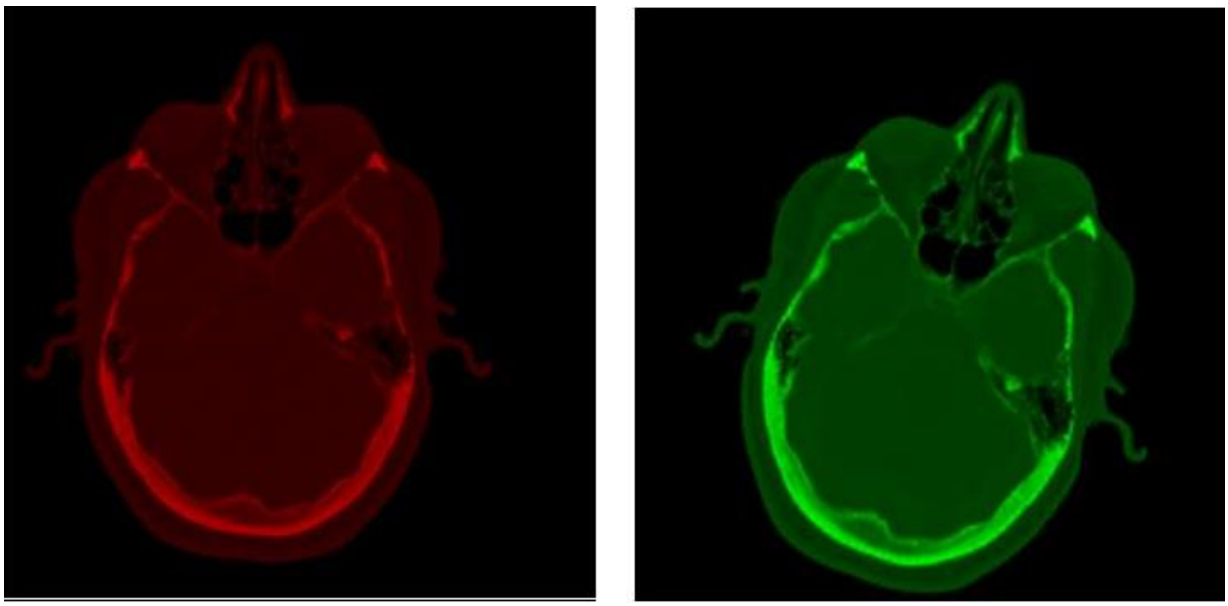
Fig. 4.3 represents the set of two CT images taken for registration. Fig. 4.4 represents the same images which are coloured just to recognize. Fig. 4.5 shows the registered image. Fig. 4.6 represents the set of two MRI images taken for registration. Fig. 4.7 represents the same MRI images which are coloured just to recognize. Fig. 4.8 shows the registered image. Fig. 4.9 represents the CT and MRI images taken for registration. Fig. 4.10 represents the CT and MRI images which are coloured just to recognize. Fig 4.11 shows the registered image.

Example 1: CT images



(a) (b)

Fig. 4.3. (a) Reference image (b) Float image



(a) (b)

Fig. 4.4. (a) Reference image coloured as red (b) Float image coloured as green

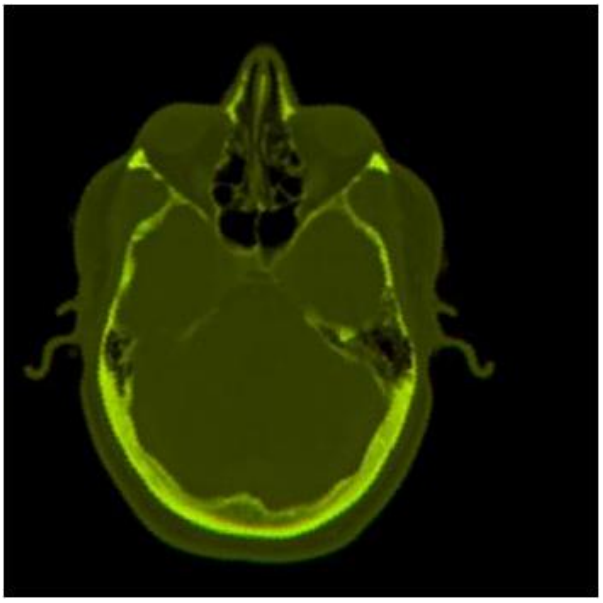
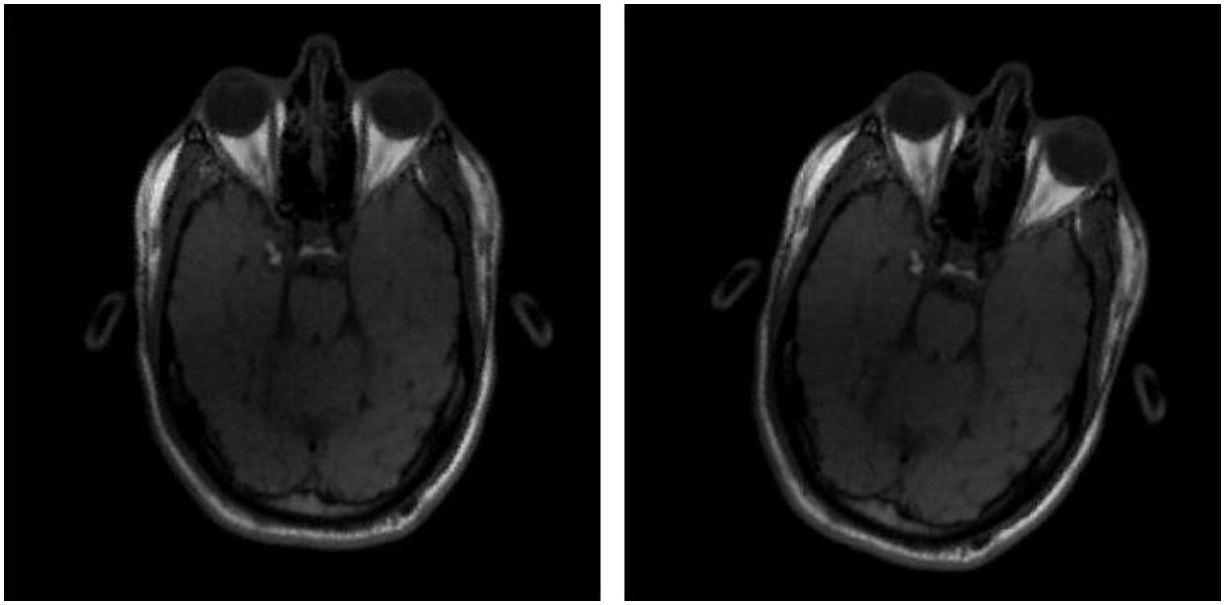


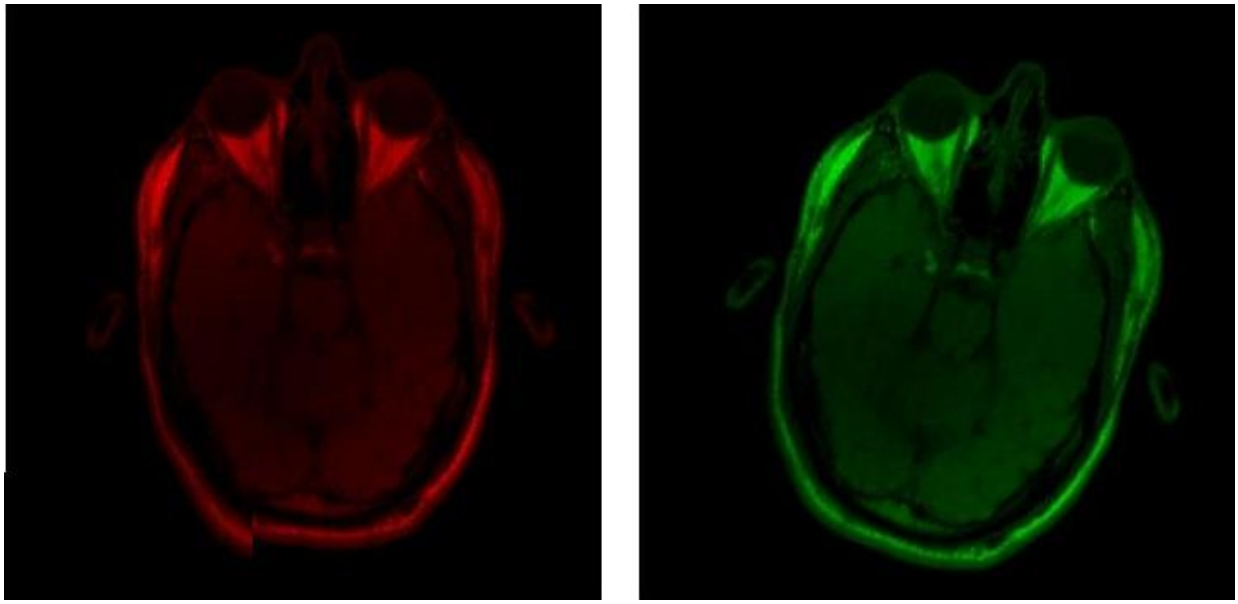
Fig. 4.5

Example 2: MRI images



(a) (b)

Fig. 4.6 (a) Reference Image (b) Float Image



(a) (b)

Fig. 4.7. (a) Reference Image with red (b) Float Image with green

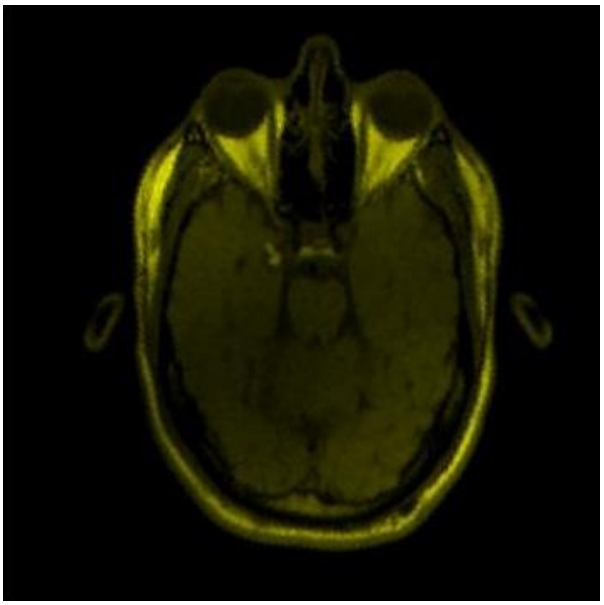
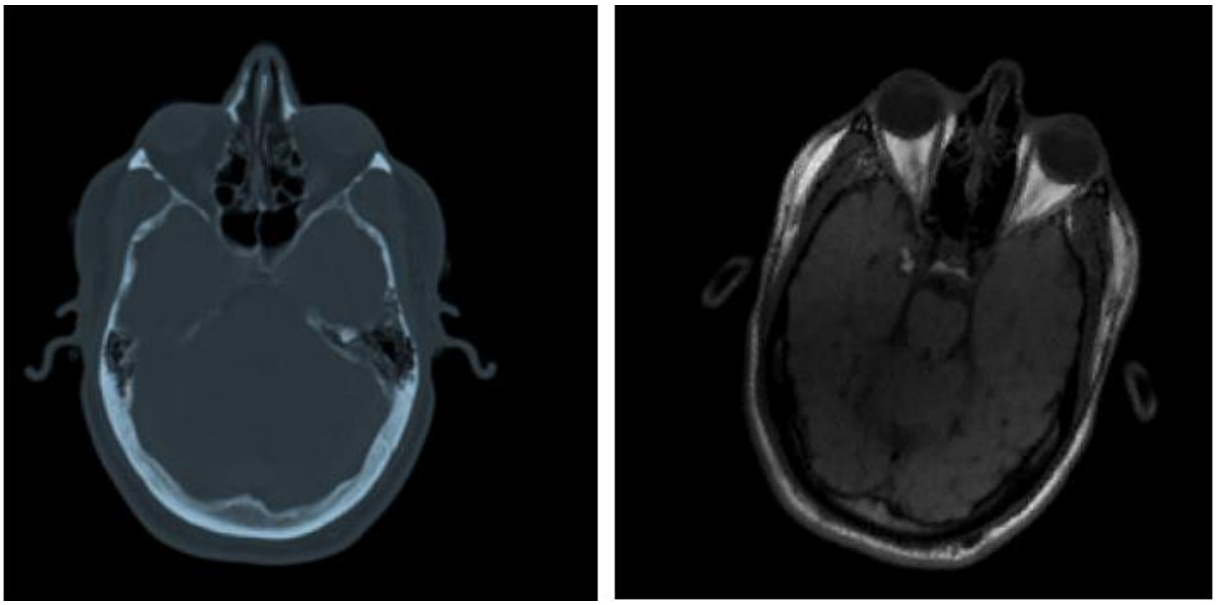


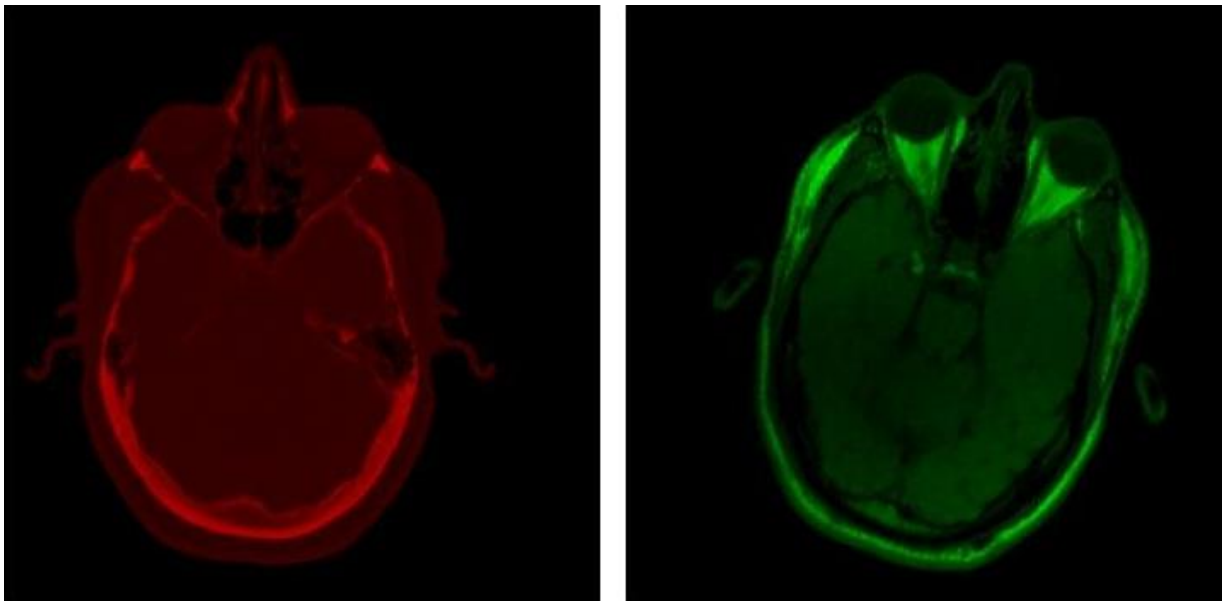
Fig.4.8

Example 3: CT and MRI image



(a) (b)

Fig. 4.9. (a) Reference Image (b) Float Image



(a) (b)

Fig. 4.10. (a) Reference Image with red (b) Float Image with green

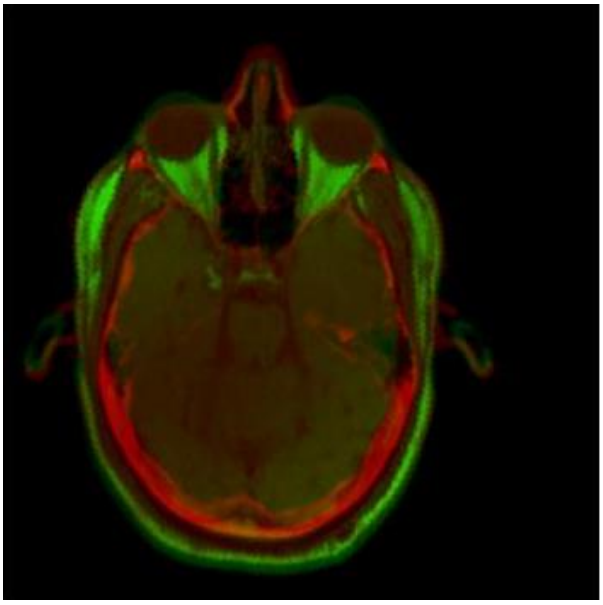


Fig. 4.11

Parameters obtained after registration are given in Table III and IV.

Table III. PARAMETERS WITH STANDARD PARTICLE SWARM OPTIMIZATION

Eg.	Maximum ECCnew	No. of iterations	RMSE
CT-CT	1.39e+05	1275	0.675
MRI-MRI	1.61e+05	1225	1.85
CT-MRI	1.69e+04	1200	8.32

Table IV. PARAMETERS WITH FAST CONVERGENCE PARTICLE SWARM OPTIMIZATION

Eg.	Maximum ECCnew	No. of iterations	RMSE
CT-CT	1.29e+05	725	0.973
MRI-MRI	1.21e+05	825	2.78
CT-MRI	1.67e+04	525	8.33

This method is based on intensity values of images. The numbers of iterations get reduced in case of Fast Convergence Particle Swarm Optimization while the result accuracy is approximately same. The number of iterations is reduced to almost two third in case of FCPSO than standard PSO. Thus, time complexity reduces and also, it reduces the chance of attraction of particles towards local minima. RMSE is high in case of multimodal images as the same part of images is represented by different intensity values.

4.5. Conclusion

A method of registration of the multimodal medical images based on normalised mutual information and spatial information is proposed. The intensity information of images is used effectively in the proposed work. As normalized mutual information is taken along with spatial information, a measure has been found which is invariant to overlapping region and is more robust measure than normalised mutual information as spatial information adds to the information between the images. The combined measure gives a good registration function. This registration function is less affected by if the sampling resolution is low. There are no

erroneous global maxima which can be obtained in case of mutual information. Also, local minima caused by interpolations gets decreased.

The method uses a global optimization technique which is better than standard genetic algorithms. Using Fast Convergence Particle Swarm Optimization, result can be obtained in a lesser time than standard PSO. The proposed approach is, thus, more robust and is an effective medical image registration method.

CHAPTER 5
CONCLUSION

Contents:

- *Conclusion*
- *Suggestions for Future Work*

CONCLUSION

This chapter focuses on the advantages and limitations of all the methods used for image registration. The scopes of future research work in this domain are also discussed.

5.1. Conclusion

Canny edge detector is the widely used edge detector as it gives thin edges. It is used in our method for detection of the edges, which helps us to easily find the contours. Contours are used for finding the principal axes of the medical rigid images. From principal axis information, eigen vectors of the inertia matrix can be found. From these two eigen vectors, the rotation angle can be found. Similarly to find scaling factor, these principal axes can be shifted in both directions so as to enclose the medical structures within rectangles. From the ratio of the heights and widths of the rectangle, scaling factors can be found in both directions. Similarly, from the translation of the centres, translation between the images can be found. This method takes very less time for computation and is time efficient. But, the problem is that it does not give accurate result. The MI based fine registration overcame this problem since it gives accurate result. As the input images to the MI based technique is already coarsely registered, it takes very less time for computation and gives finely registered images. This method is efficient and cheap but it can‘t handle the images which are not rigid structures. It works for rigid structures like brain. Also the images should have properly defined principal axes to find out the scaling factor. Thus, a feature based registration gives a course result as seen in chapter 3. Thus applying any intensity based can help us to increase the accuracy of the method. At the same time, doing so would eliminate drawback of intensity based technique (it takes large time to register the images) by reducing the search space. Thus images’ features and intensity information both are useful to find effective registration techniques for medical images. The proposed approach involves less complexity and is an effective medical image registration method.

The intensity information of images is used effectively in chapter 4. Mutual information between the images is widely used as similarity measures in many intensity based registration technique. But if the overlapping region between the images is less then MI may give an incorrect measure. The normalised mutual information overcame this problem since it is

invariant to changes in overlapping region of the two images. The measure is made more robust by including the spatial information by multiplying the gradient term with the normalised measure. The combined measure helps in the correct object identification with low probability of mismatch. For optimization, global optimization methods as better as compared to local optimization methods like powell, simplex, gradient, etc as it does not converge to into a local minima or maxima. And the method uses a global optimization technique which is better than standard genetic algorithms. But, standard PSO takes large time to converge. Number of iterations gets reduced in case of Fast Convergence PSO. The number of iterations is reduced to almost two third in case of FCPSO than standard PSO. The proposed approach is more robust, accurate and is an effective medical image registration technique.

5.2. Suggestions for Future Work

A new method for feature-based registration can be searched for an overall increase in registration performance. Different image similarity metrics can be used for refinement of automatic image registration techniques for fine registration. Also, some more techniques can be searched to further reduce the times of repetition in optimization technique of the similarity measure. The input images used for the proposed method are the planar 2-D images; it can be applied for the 3-D images as well.

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DISSEMINATION

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